Chapter 5
EV and PHEV Battery Technologies

5.1 Energy Storage Issues of PHEVs and EVs

It is well-known today that batteries are indeed the main stumbling block to driving electric vehicles. In fact, the common issues related to lithium rechargeable cells can be summed up by one simple topic: cell equalization. Typically, a battery of a HEV consists of a long string of cells (typically 100 cells, providing a total of about 360 V), where each cell is not exactly equal to the others, in terms of capacity and internal resistance, because of normal dispersion during manufacturing. However, the most viable solution for this problem might not originate from mere changes in battery properties. The aim of this chapter is, first, to explain the role of power electronics based battery cell voltage equalizers and their role in improving cycle life, calendar life, power, and overall safety of EV/HEV battery energy storage systems.

It is imperative that most studies related to energy storage systems (ESS) for HEV applications must follow a cost-conscious approach. For instance, taking into account that typical lithium batteries cost about \$500/kWh [1] (or \$250/kWh [2, 3], if manufactured in high volumes), a typical 16 kWh battery, which provides about 80 km (50 miles) autonomy to a small vehicle (simulated and tested under the Federal Test Procedure, FTP driving pattern). This amounts to a surcharge of about \$5,000 over the price of a standard vehicle, exceeding the reasonable budget for an medium consumer.

Moreover, issues related to cycle life and the calendar life issues cannot be ignored. Depending on the intensity of usage, an average cobalt or manganese cathode Li-ion battery holds about 500 cycles of 80 % the capacity, before losing 20 % of its initial capacity [4]. If the battery is replaced at that point and the cost of electricity is added, the expenses rise to \$0.1/km. Consequently, the existing scheme makes the EV option more expensive than the traditional gasoline based vehicle. Considering newer batteries based on lithium iron phosphate ($LiFePO_4$) chemistries, these numbers are slightly better, withstanding 1,000 cycles on current

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technology, and expecting (but still not proven) 6,000–7,000 cycles for future PHEV applications. On the other hand, the $LiFePO_4$ chemistry depicts slightly lower energy density (100 Wh/kg) [5, 6]. Although $LiFePO_4$ seems to be the best fit for EVs, the long term cycle life and volume costs have to be considered seriously. As a reference, current price per unit of $LiFePO_4$ ranges from $1.90 to $2.40/Wh, compared to $0.86/Wh, for typical manganese based Li-ion batteries [1–3, 5, 6]. Extrapolating the current unit price relationship to high volume applications, the battery pack for a typical medium-sized car would cost in the range of $7,000–10,000 for a 16 kWh pack.

Another critical issue to be considered is overall safety. The key factors that play a vital role in maintaining safety include, usage of high quality materials and safety monitoring at the development process. In addition, continuous monitoring of cell current, cell voltage, temperature, and taking eventual corrective measures, also helps in critically improving the safety of the system.

However, the most viable solution for today's problem might not be originated merely from changes in the battery chemistry. In fact, a much smarter solution relies on a power electronic battery cell equalizer, which can improve not only the cycle life (the quantity of charge–discharge cycles before the end of life) of batteries, but also their calendar life (the time, fully charged and no cycling, to end of life), power, and safety. In the following chapters the impact of the utilization of a battery cell equalizer is going to be analyzed, in terms of economical as well as safety advantages.

5.1.1 Battery Chemistries

5.1.1.1 Battery Parameters

To design an efficient, precise, reliable, and safe charger, parameters of the battery pack should be determined. A brief definition of battery parameters are mentioned here which will be used later.

Battery Capacity

Measured in Ampere-Hour (Ah), battery capacity indicates the amount of charge that can be drawn from a fully charged battery until it gets fully discharged. An important effect in batteries is that the higher amount of current drawn from a battery, the lower capacity the battery will have. Hence, theoretically, battery capacity is defined as the amount of current drawn from a battery that completely discharges it in 1 h. However, in practice battery manufacturers specify a table showing the amount of time the battery runs with different constant current loads and different constant power loads. In practice, this table provides more practical information rather standard definitions, because, after production different loads with different characteristics may be connected to the battery.

C Rate

This parameter is used to show the amount of current used for charging the battery. For example, for a 10 Ah battery, when it is mentioned to terminate the charging process while the charging current falls below C/10 rate (10 h rate), it means the charging should be stopped when current becomes less than the amount of current with which the battery is discharged after 10 h, or specifically 10 Ah/10 h = 1 A

State of Charge

State of Charge (SoC) is the percentage of charge available from a battery to the whole capacity of the battery. SoC is difficult to measure directly and usually some methods are used to estimate it indirectly. Besides, according to aging the rated capacity of the battery reduces over time, hence, for determining accurate SoC, the rated capacity should be measured or calculated regularly.

Depth of Discharge

Depth of Discharge (DoD) is defined as (100-SoC) in percentage, i.e., the percentage of total charge of the battery which has been utilized. This parameter is usually used in discharge patterns recommendations. For example, the battery manufacturer may recommend the user not to go over 70 % DoD according to lifetime issues.

Energy Density

Energy density can be defined based on volume or weight, i.e., Wh/L or Wh/kg. The “Volumetric Energy Density,” which is defined as the amount of available energy from a fully charged battery per unit volume (Wh/L). As we know Liter is used for measuring the volume of liquids, however, even for solid electrolytes such as Lithium Polymer batteries, the same unit is usually used. The other way of defining the Energy Density is “Gravimetric Energy Density” which is also referred as “Specific Energy” and defined as the available energy from a fully charged battery per unit weight (Wh/kg). Based on application and based on the importance of the volume or weight, either definition can be used. In the case of EVs/PHEVs usually weight is a more important factor than volume, so, mostly Specific Energy used.

Charging Efficiency

The chemical reactions inside the battery during charge and discharge are not ideal and there are always losses involved. Therefore, not all the energy used to charge

the battery, is available during discharge. Some of this energy is wasted as heat dissipation. The charging efficiency can be defined as the ratio of available energy from the battery in a complete discharge to the amount of energy needed to completely charge the battery. This parameter may be mentioned by other names such "Coulombic Efficiency" or "Charge Acceptance". In general, the coulombic efficiency for a new battery is high, however, reducing as the battery ages.

Next section discusses some aspects of different battery types used in EVs and PHEVs regarding charging. This will help in designing more efficient and flexible chargers based on battery behaviors which will finally lead to improvement of battery packs lifetime.

5.1.1.2 Main Characteristics of Commonly Used Batteries in EV/PHEV Battery Packs

Knowledge of characteristics of different battery chemistries is necessary for designing a reliable and efficient charger. There are hundred types of batteries described in reference books [7] and technical literature. Most of them are demonstration prototypes, working under laboratory conditions and still under investigation, not commercialized maybe because of costs, non-mature technology, low energy density, safety, toxic components, and so on. The most widely available batteries are Pb-Acid, Ni–Cd, Ni–MH, Li-ion, and Li-Polymer which are described below:

Lead-Acid (Pb-Acid)

For over one century, lead-acid batteries have been utilized for various applications including traction. Their well-improved structure has led to Valve Regulated Lead Acid (VRLA) batteries which can be considered as maintenance free batteries, which is a desirable characteristic for PHEVs. In terms of charge efficiency they have a high efficiency in the range of 95–99 %. The main disadvantage of Lead-acid batteries is their weight, in other words, they have a low specific energy (30–40 Wh/kg) compared to their counterparts.

Nickel Cadmium (Ni–Cd)

Considering low power applications Nickel Cadmium (Ni–Cd) batteries also benefit from a mature technology but considering traction applications their specific energy is low as well. The typical specific energy for this type is 45–60 Wh/Kg. The main applications are in portable devices, but they are also recommended when high instantaneous currents must be provided. They are typically used when long life and reasonable costs are desired. However, they have environmental concerns for recycling because they contain toxic metals [8].

Nickel-Metal Hydride (Ni–MH)

Comparing to previous types they have higher specific energy at the expense of lower cycle life. In general, for the same size batteries, NiMH batteries can have up to two or three times more energy than a Ni–Cd type. The typical value for the specific energy of the present technology NiMH batteries is in the range of 75–100 Wh/Kg. This type is widely used in EV and PHEV applications.

Lithium-Ion (Li-Ion)

This type has noticeably high specific energy, specific power, and great potential for technological improvements providing EVs and PHEVs with perfect performance characteristics such as acceleration performance. Their specific energy is in the range of 100–250 Wh/kg. Because of their nature, Li-ion batteries can be charged and discharged faster than Pb-Acid and Ni–MH batteries, making them a good candidate for EV and PHEV applications. Besides all, Li-ion batteries have an outstanding potential for long life if managed in proper conditions, otherwise, their life can be a disadvantage. One of the main reasons is almost the absence of memory effect in Li-based batteries. A weak point of Li-based batteries is safety since they are highly potential for explosion due to overheating caused by overcharging. They can almost easily absorb extra charge and get exploded. The use of advanced battery management systems (BMS) can ensure reliable range of operation of Li-ion batteries even in cases of accidents. Another advantage is that Li-ion batteries have environmental friendly materials when compared with Nickel-based batteries.

Lithium Polymer (Li-Po)

Li-Po batteries have the same energy density as the Li-ion batteries but with lower cost. This specific chemistry is one of the most potential choices for applications in EVs and PHEVs. There have been significant improvements in this technology. Formerly, the maximum discharge current of Li-Po batteries was limited to about 1C rate; however, recent enhancements have led to maximum discharge rates of almost 30 times the 1C rate, which greatly improves and simplifies the storage part of the EVs and PHEVs in terms of power density, since this can even eliminate the need of ultra-capacitors. Besides, there have been outstanding improvements in charging times. Recent advances in this technology have led to some types which can reach over 90 % SoC in a couple of minutes which can significantly increase the attraction toward EVs and PHEVs because of noticeable reduction of charging time. Because this type is a solid state battery, having solid electrolyte, the materials would not leak out even in the case of accidents. One of the other advantages of this type is that it can be produced in any size or shape which offers flexibility to vehicle manufacturers.

5.1.2 Battery Modeling and Simulation

5.1.2.1 Battery Models

Electrochemical nature of batteries has led to their highly nonlinear behavior dependent on many factors and has made it difficult to predict their characteristics such as V–I characteristic, state of charge, state of health, runtime, etc. Estimating their characteristics needs appropriate and accurate models. There are numerous battery modeling approaches and techniques in literature, each of which is more appropriate for some specific design aspects and highlighting specific effects. In general, there are many factors such as temperature, discharge current rate, age, etc. affecting the behavior of batteries. The question that arises is that for designing a transportation system or charger system "Should all these features be taken into consideration?" and if not "Which ones should be considered?" and "How much precision is required?" Numerous researches have been done about modeling of batteries for low power and very low power applications such as laptops, cell phones, battery powered digital processors, sensors, etc. In general, these studies mainly deal with behaviors of single cells or small number of cells. However, in the case of EVs/PHEVs including high power battery packs containing hundreds of cells some phenomena are exaggerated or even some can be observed only in battery packs and not in single cells, like electrical characteristics unbalance in series strings or thermal unbalance through battery pack. This shows that modeling battery packs of EVs/PHEVs needs special considerations. Unfortunately, because of their non-mature and expensive technology, not many data and experimental results are available. Hence, there seems a gap between experimentally confirmed battery models available for single cells which can be cheaply verified in any lab on one side and models of expensive battery packs of hundreds of cells with cell equalization circuits, complex controllers, protection circuits, and data acquisition systems which need to be under test for months or years on the other side. Here we first summarize and categorize different models available in the literature with specific focus on vehicular applications and finally will introduce a model which has sufficient precision and is suitable for charger application.

5.1.2.2 Electrochemical Models

Electrochemical models are based on chemical reactions occurring inside the battery cells. As a result, they are the most accurate models, since they simulate the cells at the microscopic scale. They are mostly consisted of six coupled, nonlinear differential equations. Hence, the simulations may need hours or even days of time which makes them not a good candidate for vehicular applications, since, the control systems usually need real-time data.

5.1.2.3 Stochastic Models

Stochastic models are less descriptive but more intuitive compared to the electrochemical models. They are mainly based on discrete-time Markov chains. In its simplest form, the net charge inside the battery is divided into equal charge units, each of which represents the required amount of energy for a unit to be transferred into or out of the cell.

5.1.2.4 Analytical Models

The analytical models generally use some heuristic techniques or empirical formulas to model specific characteristics of batteries. One of the simplest and oldest analytical methods is the Peukert's equation ($C = K/(I^a)$) which shows the dependence of battery capacity on the discharge rate of the battery. Some modifications can be implemented to Peukert's equation to improve it such as integrating the current. However, because of other nonlinear effects like recovery effect this equation can still have high errors in practice. An experimental setup showing the discharge effect of a Lithium-Ion battery for constant power load can be found in [9]. Another example is the Kinetic Battery Model (KiBaM). Batteries can be physically modeled as a combination of two connected reservoirs of water [10] resembling the charge of the battery as shown in Fig. 5.1 Kinetic Battery Model (KiBaM). This model evidently illustrates the relaxation effect in the batteries. Another analytical model known as Rakhmatov and Vrudhula's diffusion model [11] uses the concentration of active materials in the electrolyte as a key point in modeling process. This model shows the unavailable charge inside the

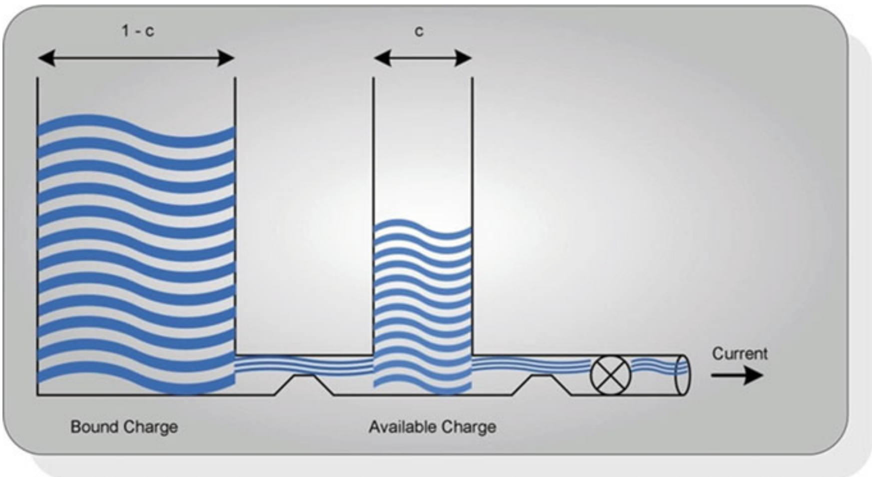


Fig. 5.1 Kinetic battery model (KiBaM)

battery and predicts the runtime of the battery. It can be proved that the diffusion model is in fact a continuous version of the KiBaM [12].

5.1.2.5 Electrical Circuit Models

The electrical circuit models generally use electrical components to model the behavior of a battery. These are the most suitable models for electrical engineering simulation purposes because of their electrical nature which makes them possible to get connected directly to the electrical network. Batteries may be modeled with a constant voltage source or a constant voltage source in series with a resistance in its simplest form, a controlled voltage source or a very large capacity capacitor. Other effects can be modeled by adding more components to the capacitor. For example, the discharge rate capacity can be modeled by adding a controlled voltage source in series with the capacitor with reverse voltage polarity and the coefficients related to different current rates can be stored in a look-up table. The above-mentioned types of battery models are oversimplified and are mainly for investigating the performance of the circuit connected to them rather than evaluating themselves. For instance, the validity of voltage source in series with a resistor is valid for limited purposes such as steady-state DC conditions and short amounts of time, since this model cannot consider the discharge of the battery. Other models, although considering more effects, still are unable to describe dynamic or transient behavior of short time constant load profiles such as pulse discharge. In general, the electrical circuit models can be mainly classified to three main categories [13]: (a) Thevenin-based models, (b) Impedance-based models, and (c) runtime-based models. The above-mentioned electrical circuit models are shown in their simple form in Fig. 5.2. More complicated ones can be found in literature.

The impedance-based models constitute a very important category and are still under investigation and need more research. They can describe the dynamic behavior of the batteries accurately and this is a very important point for battery management systems, hence, we describe them more deeply here. This model category utilizes the fact that impedance characteristics of batteries provide some information about the state of the batteries in general. This information is dependent on different factors such as SOC, temperature, life cycle and charge/discharge current, etc. The method which is used for measuring the impedance spectra is called "Electrochemical Impedance Spectroscopy (EIS)" which can be used for any electrochemical system such as fuel cells, electrochemical capacitors, ultra-capacitors, batteries, etc. This is mainly implemented by applying a small amplitude sinusoidal current or voltage signal to the system and monitoring the response for different frequencies. The reason of choosing small amplitude is to keep the system in the linear region; hence, the response will have the same wave shape with probably different amplitude and phase angle. Using the input signal and response signal, the impedance can be calculated and plotted for different frequencies. In general, there are different chemical reactions happening and

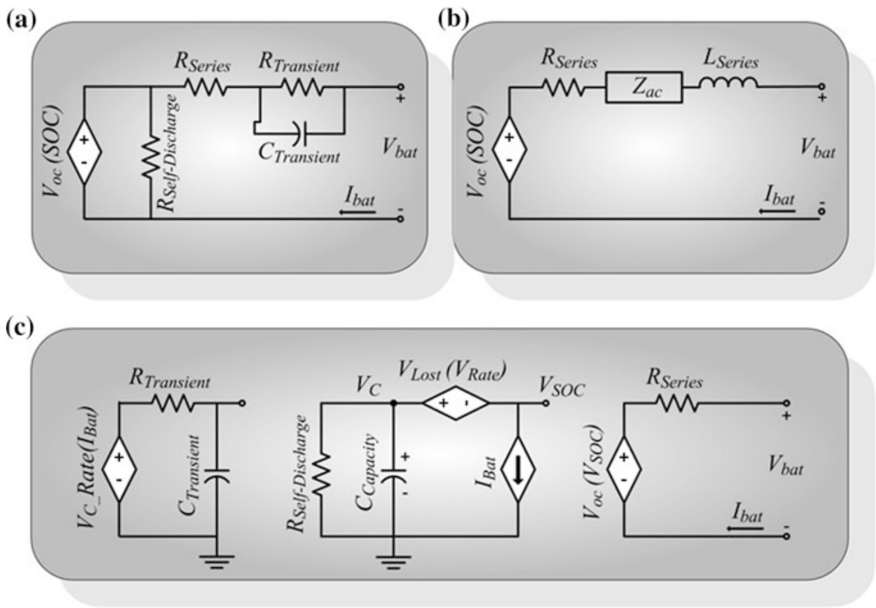


Fig. 5.2 **a** Thevenin-based, **b** impedance-based, **c** runtime-based battery models

different elements inside a battery such as solution resistance, diffusion layer, electrode double layer capacitance, electrode kinetics, etc. By applying different frequencies, some reactions keep happening and others will have lower effect and attenuate for some frequency ranges. This provides the opportunity of modeling different reactions and parameters inside the battery with different electrical components in the electrical circuit model. Despite this, still the response will be a combination of different effects and this makes the EIS analysis somewhat difficult [14]. There are different approaches for analyzing the EIS, however, the most conventional and suitable one is interpreting the results in circuit language. The complete electrochemical equivalent circuit model for Lithium-ion batteries is shown in Fig. 5.3. Other chemistries such as lead-acid may also be presented with the same configuration. Each of the elements is modeling a phenomena or element

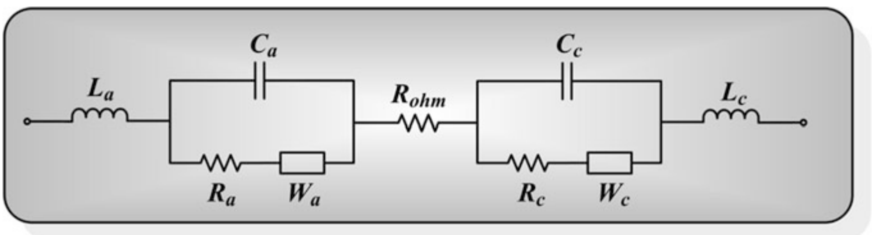


Fig. 5.3 Electrochemical equivalent circuit model

inside the battery. For example, the electrodes of the battery are porous. At high frequencies, this causes the electrodes to show an inductive behavior. The inductors L_a and L_c are modeling this behavior. The letter "a" stands for anode and "c" stands for cathode. The interpretation of other elements can be found in [15]. Other configurations are also possible, such as ladder circuit representation [16].

Choosing the circuit model configuration is the first step. The second step is to determine the values of parameters depending on the battery chemistry, Ampere-hour capacitance, SoC, type of electrodes and electrolyte, load profile, etc., in other word, system identification. There are different approaches available in the literature, one of which proposed in [16] is a universal parameterization technique which can be applied to different chemistries with different capacitance and charge/discharge ratings. Despite the effectiveness of these configurations and approaches for design purposes, sometimes they are too complex and time consuming for real-time control applications. This problem is discussed in [17] and a simplified model and identification technique suitable for real time applications is proposed, which is the case for battery management systems in EVs/PHEVs.

Another modeling approach is based on modeling the ohmic resistance of batteries. In general the internal resistance of batteries can be divided into two main parts: ohmic resistance and polarization resistance. The ohmic resistance mainly consists of electrode resistance, electrolyte resistance, separator resistance, and contact resistance. On the other side, polarization resistance is dependent on chemical polarization and electrolyte concentration. These two types of resistances are illustrated in Fig. 5.4, which is the result of applying a pulse discharge current to the battery and monitoring the voltage profile.

The immediate vertical voltage drop is due to the ohmic resistance "R_{ohm}", while the exponential voltage drop is due to the polarization resistance "R_{pol}" which happens slowly. Ohmic resistance has some information about state of the battery. For instance, higher battery ohmic resistance will cause lower battery voltage, more ohmic loss, shorter discharge time, and lower power available from the battery. Hence, modeling the ohmic resistance of a battery provides some valuable input to

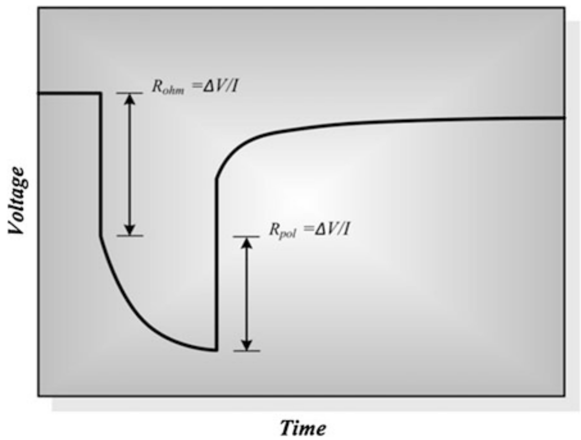


Fig. 5.4 Typical voltage response of Li-ion battery discharged by a pulse discharge current

the battery management system for better utilization of cells inside the pack which will eventually lead to better life cycle. Reference [18] investigates the relation of ohmic resistance with life cycle, discharge rate, depth of discharge, temperature, SoC, and finally comes up with a model which can be used in lifetime evaluation of batteries. Similarly [19], proposes a nonlinear resistance dependent on SoC which can add to the accuracy of the battery model while used.

5.1.2.6 Thermal Models

Another significant factor affecting battery packs performance and life cycle is temperature. Experimental results show that each 10 °C increase in the operating temperature compared to the nominal temperature of the designed battery pack will reduce the life cycle of the batteries approximately to half of the nominal life cycle. This simply shows the importance of the temperature factor. As mentioned before, there are some affects that are only observed in the battery packs and not in single cells. One of these effects is the temperature difference through a battery pack. For example, cells which are in the middle of the battery pack have higher temperature compared to those at the edges of the pack because of less ventilation. Since battery parameters change with temperature variation, different cells inside a pack will have different characteristics. This cell mismatch will significantly reduce the life cycle of the whole pack. This effect and other effects contributing to the life cycle of battery packs are investigated in [20]. This shows the need of thermal models of the battery packs which helps designing a more effective battery management system. These thermal effects are being investigated in laboratories like National Renewable Energy Laboratory (NREL) and results can be found in their reports [21, 22, 23].

The importance of temperature effects is not only for improving performance. Safety issues for Lithium-based batteries are highly dependent on temperature. Thermal runaway of Lithium-ion batteries is a very important safety point and must be considered in the battery management systems. This involves the availability of accurate thermal models of battery packs. It is worth mentioning some of the models available in the simulation softwares used for vehicular applications. One of the well-known simulators is ADVISOR by the National Renewable Energy Laboratory written in Matlab/Simulink environment. The models which have been used by this software are: (i) internal resistance model, (ii) resistance–capacitance (RC) model, (iii) PNGV capacitance model, (iv) neural network lead-acid model. Detailed description of these models and their accuracy can be found in [24].

5.1.2.7 Other Models

Battery models can be categorized based on different approaches they are driven. However, there are other important factors that battery models can be classified based on. Some of them can be mentioned as [25]: (i) the types of load profiles

supported (e.g., constant current vs. variable current or constant power vs. variable power), (ii) supported battery chemistries (Lithium-ion, Pb-Acid, etc.), (iii) battery effects that are modeled (e.g., relaxation effect, current rate capacity effect, thermal effect, etc.), (iv) computational efficiency (being fast enough for real-time control purposes), and (v) degree of precision in predicting real-life behavior of the batteries. In addition to the above-mentioned models, there are more advanced modeling techniques such as Extended Kalman Filter (EKF) for estimating the parameters of a battery model which increases accuracy especially in the case of variable current load profile which is the case for vehicular applications [26]. It is noted that Kalman filtering is a least-squares optimal estimation algorithm for linear dynamic systems where modeling and measurement errors are assumed as Gaussian white noises [27]. The algorithm recursively improves the state estimate such that the variance of the estimation error at any iteration is minimized. First, the previous state estimate and its error covariance are updated using the state-space model. Then, the updated estimate is corrected based on the latest output measurement in an optimal fashion. On the other hand, EKF is the extended form of this estimation algorithm to nonlinear dynamic systems. While the nonlinear state-space model is directly employed for the state estimate update, the other operations are done using the linearized model. Modeling the transient behavior or relaxation effect of batteries can be modeled by parallel-connected RC circuits putting in series with the battery model. By increasing the number of these brunches the accuracy of the model increases, however it causes the increased complexity and simulation time as mentioned before. In [28] it is shown that the selection of an appropriate battery model for a certain PHEV application can be formulated as a multi-objective optimization problem balancing between the model accuracy and the computational complexity. This multi-objective optimization problem is mapped into a weighted optimization problem to solve. Genetic Algorithm has also been used for battery modeling purposes. Sometimes it is very useful to derive a model based on data sheets available from manufacturers. In [29] the charge and discharge characteristics of the battery supplied by the original equipment manufacturers (OEMs) are used to find the parameters of an equivalent circuit model (ECM) for a battery. A multi-objective optimization genetic algorithm (MOOGA) is proposed to find the model parameters. This reduces the time of parameter extraction and also eliminates the need of extensive experimentation in the early phases of design. A genetic algorithm (GA), a sub-class of the larger class of evolutionary computation techniques, is a randomized search method for finding the global solution to an optimization problem, based on the principles of natural evolution, such as inheritance, mutation, selection, and so on [30]. In this method, an initial population of solution candidates evolves toward an improved generation. In each generation, the fitness of any candidate solution is evaluated to form a new population of solutions. This iteration is continued till a specific number of generations is produced and/or a satisfactory fitness level is generated [31].

5.1.2.8 Utilized Battery Model

First of all, it is important to note that every battery model is suitable for a specific application and design purpose. Having a very detailed and accurate model is not necessarily an advantage for any kind of application. The accuracy and complexity of a model should be justified for any specific application to avoid unnecessary calculations and complexity. Since our application is a battery pack charger and charging process happens during hours of time, the battery pack is a very slow dynamic system with a very big time constant compared to power electronics circuits connected to it which have time constants of time scales of milliseconds or even microseconds. This fact will be reminded during the battery modeling process. In addition, considering all the details and effects in EV/PHEV battery packs such as cell equalization circuits, sensors, controllers, thermal effects, relaxation effect, and so on is not practical since they add extra complexity to the system without any valuable advantage for designing a battery charger. This is a realistic consideration in simulation packages as well. For example, the battery model [32] used in Matlab/Simulink which we will also use for verification of our model has some limitations and assumptions such as constant internal resistance, neglecting Peukert's effect, temperature, self-discharge, and memory effect. Despite all of these limitations, this model gives very accurate results compared to practical data and manufacturer datasheets. Neglecting small differences in single cells characteristics, we can assume the battery pack with all of its components and effects as a very big single battery cell. For our simulation purposes, we have chosen the battery pack of commercialized Chevy Volt as an example which has been introduced to the market recently as a successful PHEV with a noticeable sale in North America, Europe, and Asia with lots of awards from different organizations. The specifications of this battery pack can be summarized as a 16 kWh, 45 Ah Lithium-Ion battery pack, 10.4 kWh of which is allowed to be used according to the battery management system for life cycle assurance. It consists of 288 individual cells arranged into nine modules with nominal voltage of 355 V. A typical voltage characteristic and SoC versus time is depicted in Fig. 5.5 which is obtained using Matlab/Simulink battery model with the specifications of Chevy Volt battery pack by connecting a 15 A DC current source to the battery.

For prolonging life cycle of battery packs battery management systems are usually set to operate the battery packs over 30 % and less than 90 % of SoC. This is valid also for Chevy Volt which allows the battery pack to operate only in a 60 % SoC window. If Fig. 5.5 is shown just for SoC range of 30–90 % Fig. 5.6 will be obtained.

As it can be seen from Fig. 5.6 the voltage characteristic of Li-ion battery is fairly linear with an almost constant slope for the range of 30–90 % SoC which is our SoC range of interest. This reminds of a big capacitor in parallel with a resistor getting charged by a constant current source. So we use the model shown in Fig. 5.7 as our battery model.

To find the proper value of capacitor, according to the equation $i_c = C\, \mathrm{d}V/\mathrm{d}t$ and constant current value, if the derivative of voltage is known the C value can

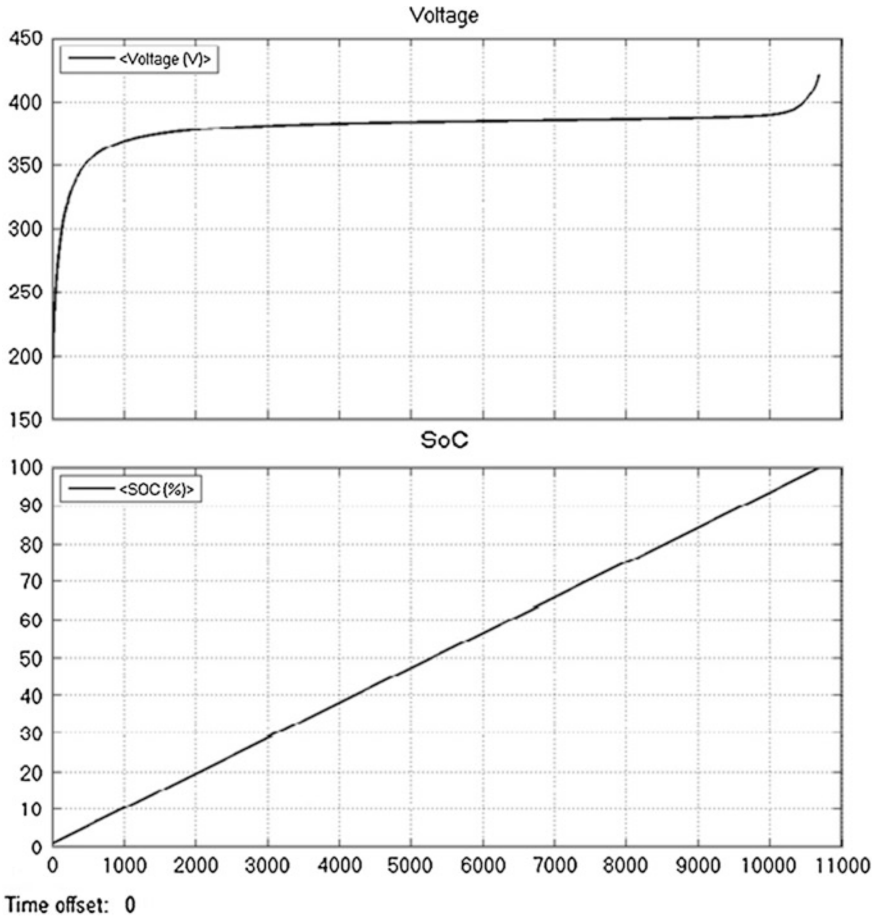


Fig. 5.5 Voltage characteristic of 45 Ah Li-ion battery

be calculated. Fig. 5.8 shows voltage derivative along with voltage and SoC. As visible in Fig. 5.8 the voltage derivative of the battery pack is around 10^{-3} (V/s) which results in a capacitor value of 15,000 F. The resistor in parallel with the capacitor may seem unnecessary; however, considering it has some advantages. First of all it can model the self-discharge of the battery pack. In addition, since most of the available power converter models assume a resistor in parallel with a filter capacitor as a load this approach is compatible with existing power converter models and minimizes the probable required modifications while connecting the battery model to the power converter which highly simplifies the modeling procedure of the overall system. The value of this resistor can be calculated based on the self-discharge rate of the battery which is dependent on the temperature and is variable for different chemistries. For Lithium-ion batteries the self-discharge rate

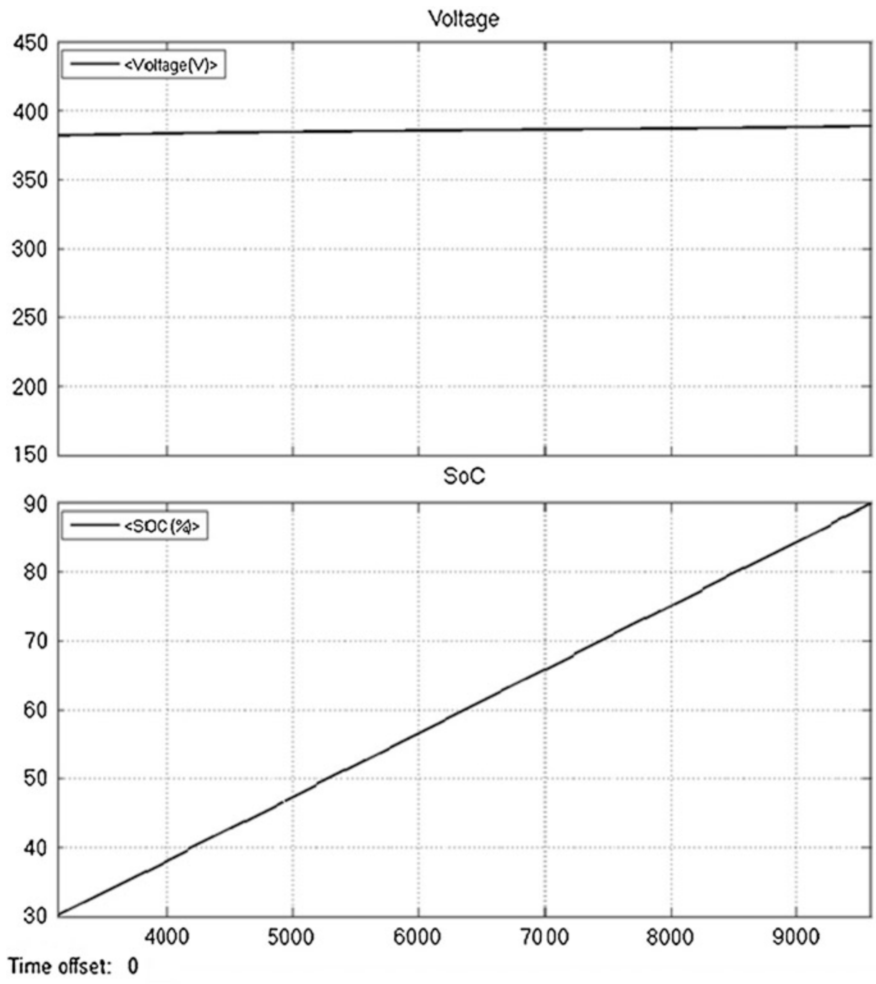
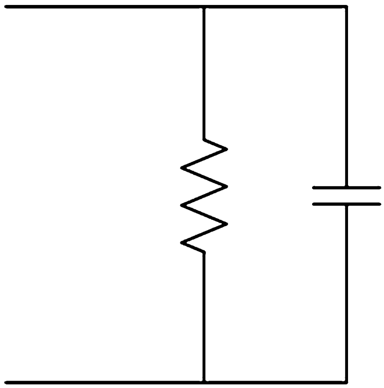


Fig. 5.6 Voltage characteristic of 45 Ah Li-ion battery from 30 to 90 % SoC

per month is 8 % at 21 °C, 15 % at 40 °C, and 31 % at 60 °C [33]. Since battery packs warm up during charging process because of generated heat and they are enclosed in a package, we assume 40 °C for our calculations as a reasonable average temperature.

During self-discharge according to the battery model, the capacitor is discharging through the parallel resistor, so a simple KCL equation results in $dV/dt = V/(R \times C)$. Since the charge in a capacitor is linearly dependent to the voltage of the capacitor ($q = C \times V$), self-discharge can be measured using the voltage. According to Fig. 5.7 voltage of the battery pack at 90 % SoC is around 390 V. According to 15 % per month rate of discharge, the battery pack voltage will

Fig. 5.7 Parallel RC battery model



decrease around 0.15 × 390 V = 58.5 V per month. Using the KCL equation mentioned above (58.5/(30×24×60×60) = 390/(R×15,000)) the resistor value will be calculated as around 1,150 Ω.

To verify the validity of the derived model with the parameter values calculated above, the results from the battery model in Matlab along with the results from the parallel RC model are shown on the same plot as in Fig. 5.9. The continuous black line shows the results from Matlab battery model and the dashed magenta line shows the data from parallel RC model with calculated parameter values. First row of Fig. 5.9 shows the voltage of the battery, second row shows the SoC change, third row represents the voltage derivative versus time and forth row explains the voltage error between two models. There may seem a big difference between voltages and voltage derivatives and huge voltage error, however, if we consider only from 30 to 90 % SoC **Fig.** 5.10 will be obtained which shows very good match between two models. As visible from **Fig.** 5.10 the voltage error between two models is less than one volt which means less than 0.3 % error which is a great match.

5.1.2.9 Summary

In this chapter, battery parameters such as capacity, C rate, SoC, DoD, etc. which are used to characterize batteries were introduced. Characteristics of commonly used batteries in vehicular applications such as Lead-Acid, Nickel Cadmium, Nickel-Metal Hydride, Lithium-Ion, and Lithium Polymer were studied. Different chemistries may need different charging methods. Various charging schemes such as constant voltage charging, constant current charging, taper current charging, pulse charging, reflex charging, and float charging were mentioned. It is very important to terminate the charging process on time in order to avoid damaging expensive battery packs. Several termination methods were reviewed including time, voltage, voltage drop, current, and temperature.

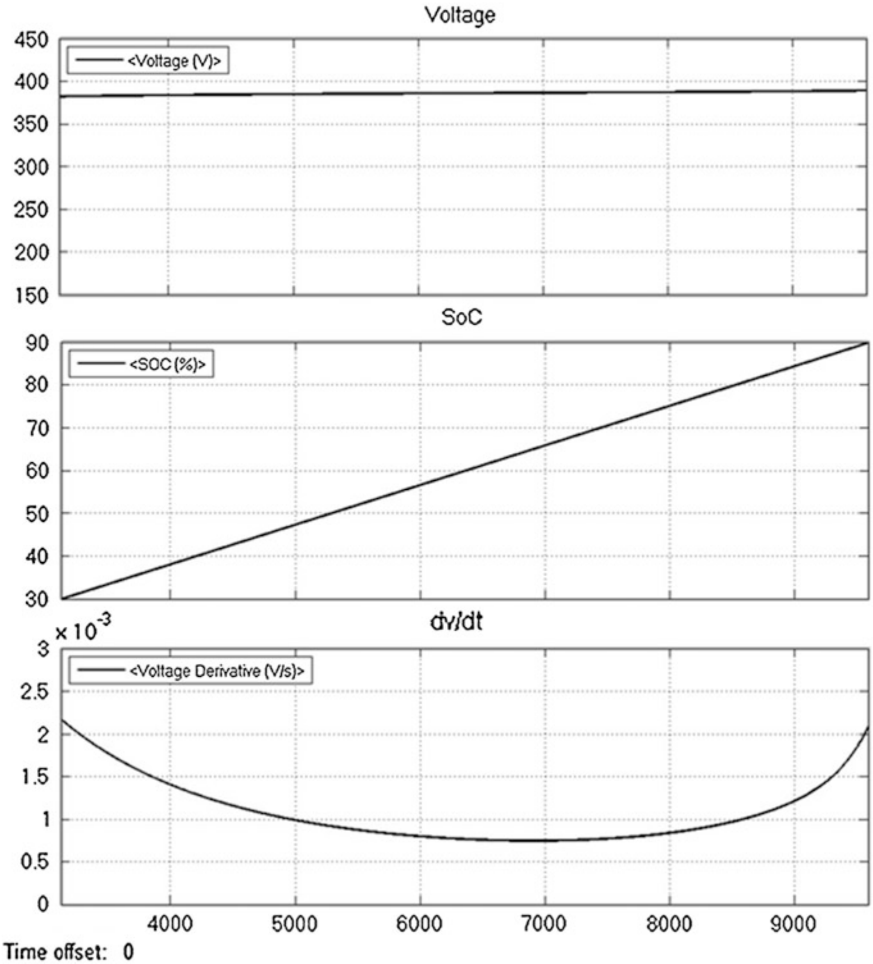


Fig. 5.8 Voltage characteristic and derivative of 45 Ah Li-ion battery from 30 to 95 % SoC

Cell balancing which is a very important issue in extending the life time of battery packs was described and its effects were investigated. Different cell balancing techniques such as charging, passive, and active were studied. Importance of SoC estimation in the performance of battery charger was mentioned and different SoC estimation techniques such as complete discharge, ampere-hour counting, measurement of physical characteristics, open circuit voltage, and soft computation techniques were investigated. Charging algorithm was defined and a typical charging algorithm for Lead-Acid batteries were mentioned.

Not only the performance and accuracy of the battery charger highly depends on the battery model, for designing any type of system the model of the load

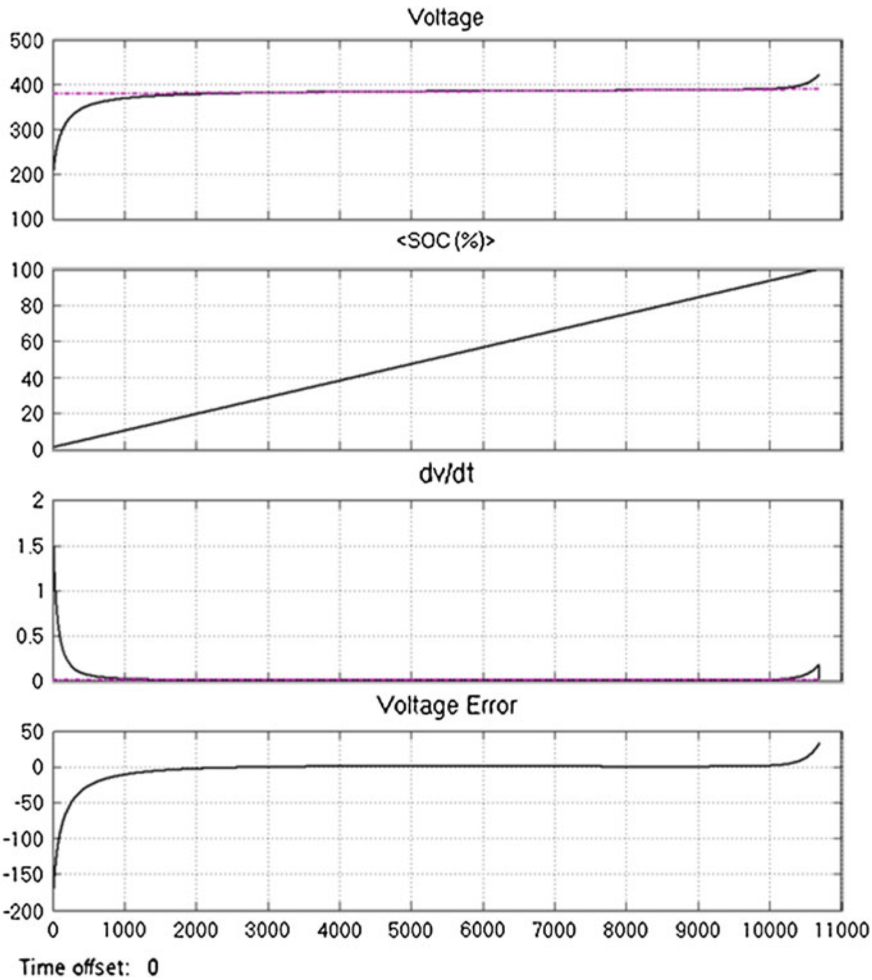


Fig. 5.9 Simulation results for matlab battery model and parallel RC model for 100 % SoC window

should be appropriately selected to ensure reliable and efficient performance of the system. Various types of battery models such as electrochemical models, stochastic models, analytical models, electrical circuit models, thermal models, etc., have been comprehensively investigated in this chapter. According to our application and the required accuracy a simplified battery model has been utilized which shows acceptable accuracy.

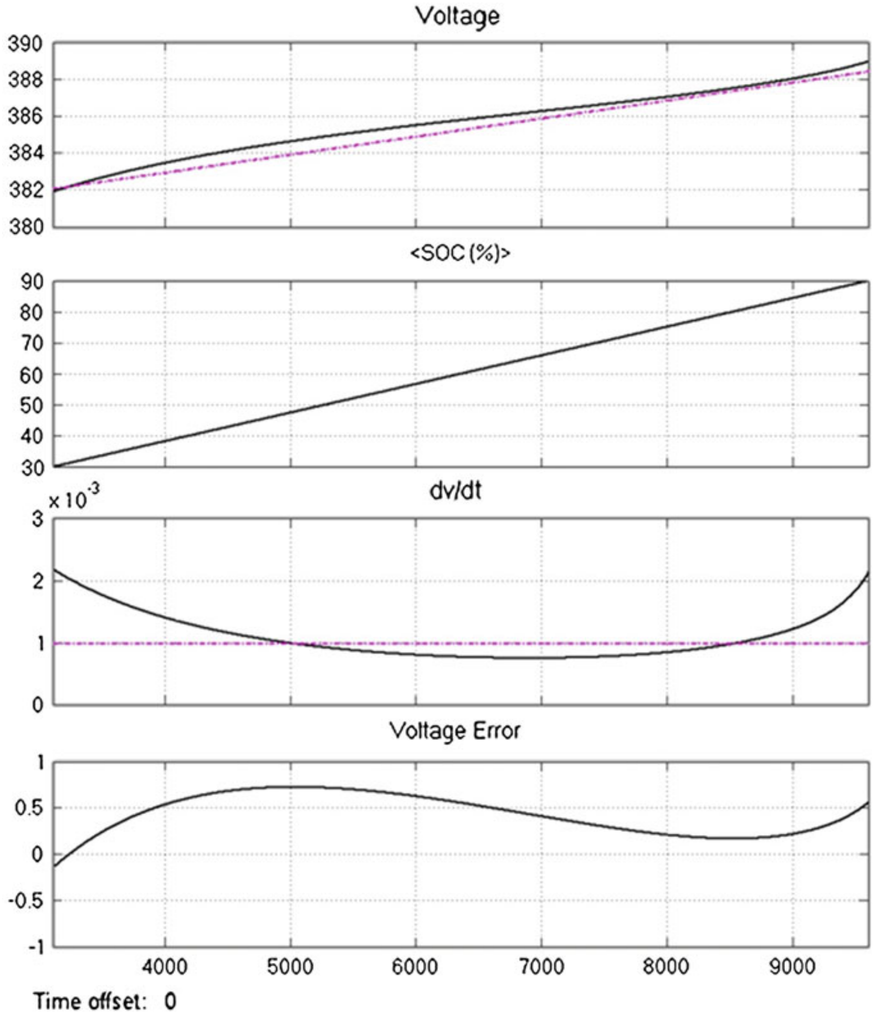


Fig. 5.10 Simulation results for matlab battery model and parallel RC model for 60 % SoC window

5.1.3 Lithium-Ion Batteries

5.1.3.1 Introduction to Lithium Batteries

Lithium rechargeable battery technologies, although not mature enough to be used in EV/PHEVs, prove to be the best solution for PHEV applications today. For instance, a 20 kWh lithium-ion battery weighs about 160 kg (100–140 kWh/kg), which is acceptable for PHEV applications. In contrast, current HEV Nickel-Metal Hydride (Ni–MH) batteries weigh between 275 and 300 kg, for the same

application. Moreover, Li-ion batteries also depict excellent power densities (400–800 W/kg) [3], allowing more than 2C discharge rate. "C" represents the discharge of full capacity in 1 h (at the rate of 40–80 kW peak power, in a 20 kWh pack), and up to 10 C for some chemistries [5, 6]. However, they also suffer from many drawbacks. One of them is the cost (projected at about $250–$300/kWh; $600/kWh for the $LiFePO_4$ chemistry), which is the most expensive of all chemistries [1, 3]. The second drawback is that lithium is a very flammable element, whereby its flame cannot be put off with a normal ABC extinguisher [34]. Finally, Li-ion batteries have a cycle life between 400 and 700 cycles, which does not satisfy HEV expectations [3]. Therefore, finding a solution to these issues is extremely crucial.

In order to resolve safety issues, few manufacturers have modified the chemistry of the battery [5, 6]. This is currently the case for Lithium iron phosphate ($LiFePO_4$) batteries, which seem to have handled few issues related to EV applications, such us reducing flammability and obtaining higher cycle life (1,000 cycles or more) [5, 6], but the higher cost and equalization issues are still pending to be resolved.

With reference to cycle life, the battery can suffer significant degradation in its capacity, depending on its usage. Furthermore, the internal resistance also increases with each charge cycle. Also, according to the chemistry and the quality of the cells, a battery typically loses about 20 % of its initial capacity after about 200–2,000 full cycles, also known as the 100 % SOC cycles. The cycle life can be greatly increased by reducing SOC, by avoiding complete discharges of the pack between recharging or full charging. Consequently, a significant increase is obtained in the total energy delivered, whereby the battery lasts longer. In addition, over-charging or over-discharging the pack also drastically reduces the battery lifetime [35–42].

5.1.4 Characteristics of Lithium-Ion Batteries

Lithium-ion batteries have noticeably high specific energy, specific power, and great potential for technological improvements providing EVs and PHEVs with perfect performance characteristics such as acceleration performance. Their specific energy is in the range of 100–250 Wh/kg. Because of their nature, Li-ion batteries can be charged and discharged faster than Pb-Acid and Ni–MH batteries, making them a good candidate for EV and PHEV applications. Besides all, Li-ion batteries have an outstanding potential for long life if managed in proper conditions, otherwise, their life can be a disadvantage. One of the main reasons is almost the absence of memory effect in Li-based batteries. A weak point of Li-based batteries is safety since they are highly potential for explosion due to overheating caused by overcharging. They can almost easily absorb extra charge and get exploded. The use of advanced battery management systems (BMS) can ensure reliable range of operation of Li-ion batteries even in cases of accidents. Another advantage is that Li-ion batteries have environmental friendly materials when compared with Nickel-based batteries.

5.1.5 Cycle Life Versus State of Charge

5.1.5.1 Cycle Life versus SOC

In the context of this section, 100 % SOC is the state of a cell after being fully charged at 4.2 V per cell, and 0 % SOC corresponds to the state of a fully discharged cell (3 V per cell). The initial Capacity (C) is the capacity during the first few cycles that go from 100 to 0 % SOC, and the cycle life is the amount of cycles after the cell loses 20 % of its initial capacity.

If the battery is initially not fully charged, and not fully discharged during the discharge period and before charging again, then the full capacity is not used. Contrary to the Ni–Cd batteries, in lithium batteries this is actually beneficial to the cell. In fact, the cycle life is greatly increased.

In Fig. 5.11a, the cycle life of several available cells in the market are shown, under different SOC during the cycle. It can be appreciated how cycle life increases as SOC utilization is reduced. In this case, SOC utilization is considered to be centered around 50 % SOC, or half charge. This is also confirmed by Fig. 5.11b, where the total energy delivered during the cell lifetime is also higher when SOC reduces. The latter is expressed in C units (initial capacity under 100 % SOC).

The trend curves are critical for economical analysis. They are estimated based on the tests performed by [35–43]. Each point represents the value during a test performed on multiple reference sources, and the dotted line is the calculated trend of all those values. The plots of Figs. 1–4 can also be the subject matter for further analyses. For example, in 360 V HEV batteries, a string of 100 cells is used. In this simulation, a 5 % initial dispersion (σ) in the capacity of the cells is considered, charging the pack at 4.1 V per cell (86 % SOC), and discharging at 72 % of the total capacity (up to 14 % SOC). An interesting trend can be observed. The smaller capacity cells swing initially from about 92–8 % SOC, which is 84 % of the total capacity, instead of the average 72 %. This higher SOC swing can be translated into less cycle life (282 cycles, instead of 600), which is a deeper degradation for the smallest capacity cells.

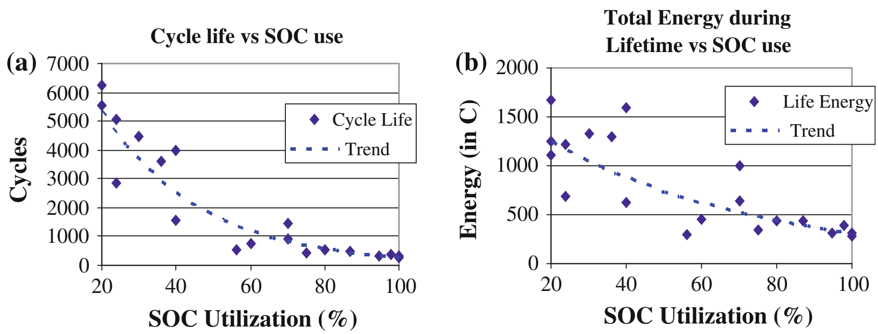


Fig. 5.11 **a** Cell cycle life versus SOC utilization; **b** cell total energy delivered during total lifetime versus SOC utilization

This effect deepens during successive cycles, producing a premature degradation of smallest capacity cells, which brings the whole pack into a premature "out of service." Figure 5.12a shows the distribution of SOC (quantity of cells vs. SOC) at the end of discharge, in steps of 47 cycles. Figure 5.12b shows the distribution of SOC (quantity of cells versus SOC) at the beginning of discharge, in steps of 47 cycles. The gradually increasing SOC span is an indication of the reduced capacity.

From Fig. 5.12, it is clear that the end of life arrives faster, because of the initial dispersion in capacity. Another critical inference that can be drawn is that the dispersion increases with cycle life. In this case, 282 operation cycles causes the smallest capacity cell to completely discharge, even if the demanded capacity is 72 % of the nominal capacity. The average capacity cell, on the other hand, withstands 602 cycles of 72 % nominal capacity, before overcharging or overdischarging. Although, this cycle life is better, it is still not enough from the point of view of PHEV energy storage applications.

Throughout this chapter, several issues related to lithium batteries, for EV/HEV/PHEV applications, have been exposed, particularly the unbalance in SOC among cells. It is clear that there can be considerable improvements in lifetime of a battery pack, if all cell capacities are suitably matched. A practical solution to obtain cell equalization exists in the form of an electronic cell equalizer. In Chap. 6, the most common equalizer topologies are reviewed.

5.1.6 Solutions to Keys Issues

An alternative way to solve the above-mentioned problems, which are essentially common to the all lithium rechargeable batteries, is using electronic control, in the form of cell voltage equalizers. Few of the control rationales are briefly listed below.

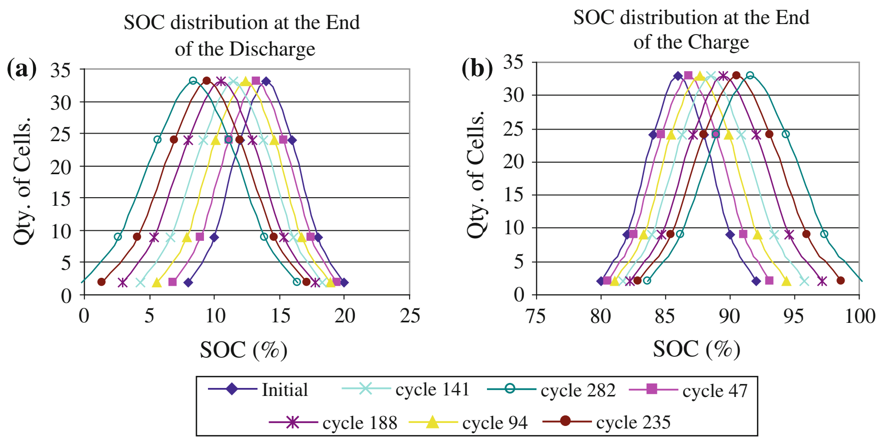


Fig. 5.12 **a** Cell distribution of SOC in a pack, with initial σ = 5 %, at the end of discharge; **b** cell distribution of SOC in a pack, with initial σ = 5 %, at the end of charge

5.1.6.1 Over-Voltage Protection

This functionality cuts charging current when the total voltage is more than 4.3 V per cell. This is because, at higher voltages, metallic lithium is formed inside the cell [35], which is highly flammable, as explained earlier [34]. For the sake of simplicity, this protection is sometimes applied to the whole pack of cells, instead of measuring the voltage of each cell.

5.1.6.2 Under-Voltage Protection

This functionality cuts discharging current when voltage is under 2.5 V per cell. Under this voltage, some capacity fades, and a specific quantity of unwanted copper plating is formed inside the cell [36]. This unwanted copper may generate internal short circuits. Also in this case, for the sake of simplicity, the total voltage might be measured, instead of verifying the voltage of each cell.

5.1.6.3 Short Circuit or Over-current Protection

This protection scheme disconnects the charging/discharging current if it is over a certain limit (2–50 ℃, depending on the cell technology) [43].

5.1.6.4 Overheating Protection

There are two reasons as to why it is recommended to avoid working at high temperature: First is safety, because of the lithium flammability [34]. The second is degradation of the capacity increases with higher cell temperature. In this case, current stops flowing, if pack temperature rises over a certain value (about 60 °C) [43].

5.1.6.5 Cell Voltage Equalizing

Using a simple cell voltage equalizer, based on heat dissipation (using a resistor), some of the excessive power from the higher voltage cell can be successfully purged. Due to heating problems that this method may involve, the discharging current must be relatively small (about 300 mA, depending on the capacity of the pack).

Although these protection functionalities are useful, they prove to be highly insufficient. In fact, the differences in capacity and internal resistance from cell-to-cell, within the same pack, may result in unwanted voltage peaks, especially during the final stages of charge and discharge. For example, during the charge of a battery pack, due to differences among the cells, a smaller capacity cell will

finish with a voltage higher than the average. Depending on the protection circuitry, usually controlled by the total pack voltage, this situation may not be detected, and even if detected, the protection will simply cut the charger, reducing the battery capacity and not solving the issue at hand. A resistive equalizer will only reduce the voltage of the overcharged cell gradually, but it will not be able to avoid degradation of the cell.

A similar situation occurs during discharge. The lower capacity cell suffers from over-discharge, which is not detected by the protection circuit. Furthermore, the reduced capacity cell goes into overcharge and over-discharge. Thus, it suffers from additional capacity reduction and the cell rapidly deteriorates, which downgrades the overall capacity of the pack.

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